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HOW SOCIAL MEDIA ADVERTISING AND REPETITIVE MARKETING MESSAGES AFFECT THE ONLINE PURHASING BEHAVIOR?

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Abstract

In the past decade social media advertising has disrupted the marketing and advertising totally.

As social media advertising platforms such as Facebook offer easy, effective and relatively cheap services, they have enabled and encouraged the rise of new kinds of companies operating solely online by tapping into the potential of easily reaching the audience and attracting them to their webstores. This has made it possible for up and coming companies with less well-known brands to attract customers and build up their brands.

Naturally as the marketing field has been disrupted by the social media advertising, the traditional rules and guidelines of marketing need to be re-evaluated requiring academic research to understand how social media marketing and people's behavior online differs from more traditional channels. Additionally, the ability to effectively personalize the marketing messages for different audience groups for example based on the previous engagement or other online behavior brings up another layer to the phenomenon.

For the purpose of this study, the audience visiting the webstore of the case company is divided based on their previous brand engagement to three groups; fresh audience with no previous engagement, retargeted audience with some engagement for example on social media platforms or website visits and returning audience with previous webstore visits. Fresh and retargeted audience groups ended up to the webstore via Facebook advertisements while returning audience returned to the site without the need of extra marketing activities.

With t-tests and ANOVA it was possible to establish differences in behavior between these groups and based on that, regression models were created to further understand the drivers affecting conversion rate and revenue per user.

What comes to the reactions to the Facebook advertisements, people with previous brand engagement, i.e. retargeted audience was much more likely to enter the webstore by clicking the advertisement than fresh audience. Additionally, retargeted audience has higher conversion rate and higher revenue per user values as well. As previous research has also found, previous engagement with the brand is indeed the strongest indicator for purchase intention. In addition to that, returning audience i.e. the people who return to the website on their own have the highest conversion rates and revenue per user values out of the audience groups studied. It is likely that this can be explained with the stronger firm-consumer relationship, making this group the most loyal and profitable customers.

For the fresh and retargeted audience groups, time spent on the website has positive affect on both conversion rate and revenue per user. So, it seems that when previous engagement with the brand is lower, clicking the Facebook advertisement and spending more time on the website builds up the firm-customer relationship and improves purchase intention.

Keywords Social Media Marketing, Advertising, Online Shopping Behavior, Retargeting

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Tiivistelmä

Viimeisten kymmenen vuoden aikana sosiaalisen median mainonta on pakottanut markkinoinnin ja mainonnan uudistumaan totaalisesti. Koska sosiaalisen median alustat kuten Facebook tarjoavat helppoja, tehokkaita ja suhteellisen halpoja palveluja, täysin uudenlaisten, pelkästään internetin välityksellä toimivien uusien yritysten joukko, jotka käyttävät Facebookin kaltaisia alustoja ihmisten houkuttelemiseksi verkkokauppoihinsa on kehittynyt. Tämä on avannut uusia mahdollisuuksia nouseville ja vielä tuntemattomille yrityksille tavoittaa asiakkaita ja rakentaa brändiään.

Luonnollisesti sosiaalisen median aiheuttama vallankumous markkinoinnissa vaatii vanhojen teorioiden ja sääntöjen tarkastelua uudessa ympäristössä. Akateemista tutkimusta tarvitaan, jotta voidaan kehittää ymmärrystä siitä, miten sosiaalisen median markkinointi ja ihmisten käyttäytyminen internetissä poikkeaa perinteisemmistä kanavista. Lisäksi, mahdollisuus tehokkaasti yksilöidä markkinointiviestejä eri asiakasryhmille esimerkiksi aikaisemman brändikanssakäymisen tai muun käyttäytymisen perusteella tuo ilmiöön uuden kulman.

Tätä tutkimusta varten case-yrityksen verkkokaupassa käynyt yleisö jaettiin kolmeen ryhmään aikaisemman brändikanssakäymisen perusteella. Uudella yleisöllä ei ole aikaisempaa kanssakäymistä brändin kanssa, uudelleentargetoidulla yleisöllä on esimerkiksi aikaisempaa kanssakäymistä yrityksen sosiaalisen median sisällön kanssa tai aikaisempia käyntejä yrityksen verkkokaupassa ja palaava yleisö on käynyt aikaisemmin yrityksen verkkokaupassa. Lisäksi uusi ja uudelleentargetoitu yleisö päätyivät yrityksen verkkokauppaan klikkaamalla mainosta Facebookissa. Palaava yleisö palasi verkkokauppaan itse, ilman tarvetta markkinointitoimenpiteille.

T-testien ja ANOVA-analyysien perusteella oli mahdollista todistaa, että asiakasryhmien käytöksissä oli eroja. Tämän lisäksi regressiomalleilla pyrittiin tarkemmin ymmärtämään mitkä asiat vaikuttivat verkkokaupan kävijöiden konversioasteeseen ja tuloihin per asiakas.

Mitä tulee Facebook-mainonnan tehokkuuteen, yleisö, jolla oli aikaisempaa kanssakäymistä, eli tässä tapauksessa uudelleentargetoitu yleisö, huomattavasti todennäköisemmin klikkasi Facebook-mainosta ja päätyi yrityksen verkkokauppaan. Lisäksi uudelleentargetoidulla yleisöllä oli korkeampi konversioaste ja koreampi tuotto per asiakas kuin uudella yleisöllä. Aikaisempaa tutkimusta tukien aikaisempi brändikanssakäyminen on paras indikaattori ostoaikomukselle. Tutkituista asiakasryhmistä, palaavalla yleisöllä, eli yleisöllä, joka palasi verkkokauppaan itsekseen oli kaikista korkeimmat konversioaste ja tuotto per asiakas. On todennäköistä aikaisempaa tutkimusta tukien että tällä asiakasryhmällä on vahvin suhde brändiin ja yritykseen, tehden tästä ryhmästä yrityksen lojaaleimmat ja tuottavimmat asiakkaat.

Uusille ja uudelleentargetoiduille asiakkaille verkkokaupassa käytetty aika korreloi sekä konversioasteen, että asiakaskohtaisen tuoton kanssa. Näyttää siltä, että heikomman aikaisemman brändikanssakäymisen omaavalle yleisölle Facebook-mainoksen klikkaaminen ja verkkokaupan selailu vahvistaa sidettä brändiin ja yritykseen ja lisää ostohalukkuutta.

Avainsanat Sosiaalisen median markkinointi, Mainonta, Verkko-ostokäyttäytyminen, uudelleentargetointi

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1. INTRODUCTION

The global emergence of social media platforms has fundamentally changed the way people interact online and communicate to each other (e.g. Kumar et al., 2015). The massive number of people using the few industry leading platforms like Facebook and Instagram has naturally also attracted companies that wish to utilize the ability to potentially reach the over two billion active monthly users (Facebook, n.d. and Statista, 2019).

In addition to the ability to reach the hundreds of millions of people using the social media services, for example Facebook has developed truly groundbreaking personalization and especially targeting tools for companies that have very much disrupted the field of marketing and forced companies to re-think their marketing and advertising strategies to better take advantage of these new tools that help them better pin point personalized messages to different audience groups (e.g. Kumar et al., 2015).

On top of all that, Facebook advertising is also very affordable, further encouraging companies to incorporate social media as one of the main marketing channels used.

As the companies spend more and more money to get visibility on Facebook's platforms, it is important to try to understand how these new marketing tools work and how they differ from the more traditional channels. Many academic studies have been conducted on for example how social media exposure to the firm-generated content shapes people's perception of the company (e.g. Hanssens et al., 2014) or what type of content is the most effective for gaining people's attention (e.g. Kantola, 2014), but truly overarching studies on the effect that Facebook advertising has on webstore purchasing behavior and especially how repetitive marketing messages work are still very rare and very specific for their case studies like for example Lambrecht and Tucker, 2013.

However, as social media advertising has become as huge phenomenon as it is, it is crucial to study how these marketing activities shape the brand relationship and purchasing behavior of consumers in the long run.

The purpose of this study is to investigate how social media advertising and especially exposure to repetitive marketing messages online shape the purchasing behavior on the online store. This will be studied by combining and analyzing data on customer behavior gathered from the Facebook advertisement campaigns and webstore site analytics of the case company.

As most of the academic papers used as a basis of this study have focused on sort of one-time effectiveness of the advertisement (like e.g. Kantola, 2014 and Hanssens et al., 2014), this study aims to provide new understanding on how the purchasing behavior changes when the audience groups are retargeted with advertising based on their initial responses. This is especially useful in terms of the managerial implications as social media activities of companies are also widely seen as a customer relationship management activities and companies aim to establishing interactive and engaging customer relationships online that then lead to brand loyalty and profitable customer relationships.

1.2. Case Company Introduction

The case company (from now on referred as company X) for this study is a small, Finnish fashion company that sells accessories, mainly sunglasses and watches. Characteristic making these products really unique and special is that all of them are made of wood. The company emphasizes Finnish design and Finnish materials in their marketing communications and underlines the connection the products have to Finnish nature.

As the company X is rather small and still up and coming, it does not have very well-known brand to leverage. Due to that, a large portion of the marketing efforts is focused on building up brand awareness. Another rather unique characteristic of the company is that it operates entirely online, meaning that the company only sells its products on its own webstore. In addition to that, the company only utilizes online channels for marketing, the Facebook and Instagram being the main channels, along with Google advertising and other channels that play smaller role in marketing.

This solely digital existence creates a very interesting setting for analyzing marketing efforts of the company X, as the online channels, mainly Facebook and Instagram are the only way for the company to reach both existing and potential customers and try to engage them and create sales.

To further highlight the specialty of this case company and this study as a whole, the current academic literature usually considers the online channels like social media as a part of the multi-channel marketing toolkit for the companies emphasizing the synergies and different roles of each channel. This is while in reality especially the up-and-coming companies with limited resources might only utilize the social media as their marketing channel due to the perceived effectiveness compared to the costs. These new kinds of companies and their practices pose challenges to the current understanding on advertising, marketing strategy and customer relationship management making this study very relevant for the future of marketing strategy by offering new insights into advertising and effectiveness of marketing activities.

2. THEORETICAL BACKGROUND

In this section the relevant existing literature and frameworks will be discussed in order to have strong academic understanding on the phenomena studied. The theoretical background is divided into a few main themes, but as most of them are interlinked in many ways, it is impossible to discuss them in isolation from each other, making this chapter a bit repetitive as it aims to create as comprehensive understanding on social media advertising as possible. In a nutshell the theoretical framework develops around gathering understanding on relevant literature to answer the research questions which are:

1. What is the effect of repetitive marketing messages (i.e. retargeted advertisements) on social media?

2. How the previous engagement with the brand influences the response to advertisements and online purchasing behavior?

2.1. Customer Engagement

The worldwide internet usage and information accessibility has reduced the power companies hold over their brands and products. As everyone can voice their opinions online, the customer relationship management has become more equal, both companies and customers have voice and power to voice their opinions to others. Kumar & Bezawada (2014) broke customer participation into two, customer engagement and customer interaction, where engagement was described as signing up to follow company's social media site and interaction was defined as contributing to the social media by liking, commenting and sharing content. Other studies (like Kumar et al., 2011) consider Kumar & Bezawadas customer interaction also as a part of customer engagement as it can be argued that passive following of company's content is not true engagement. For this study, customer engagement will be defined as a combination of customer engagement and customer interaction defined by Kumar & Bezawada. So, in essence what companies want to achieve by creating customer engagement is positively influence consumers' brand consideration. Customer engagement (for example likes and comments on Facebook) on company's content validate the brand to other consumers, creating more positive attitude towards the brand and engaging with it (Sanne & Wise, 2018). Positive attitude towards brand encourages engagement and cultivates stronger relationship with the brand, resulting in content-creation like liking, commenting or writing reviews (the customer interaction that Kumar & Bezawada (2014) described) (Sanne & Wise, 2018). Over time the customer engagement leads to higher customer loyalty (Campbell and Keller, 2003, Palmatier et al., 2006), higher customer lifetime value (Kumar et al., 2015) and encouraging others to engage with company (Sanne & Wise, 2018). The possibility to reach virtually everyone on social media and have two-way communication with the audience encourages companies to invest resources on social media in pursue of the lucrative benefits described before.

2.2. Social Media Advertising – Facebook

With the increased usage of internet and especially social media, the content on the platforms like Facebook may potentially reach hundreds of millions of users. According to Facebook (n.d.) they have 1.47 billion active daily users worldwide. As the social media platforms are typically free to use to attract users, they tend to make their money mainly from the advertisements shown to the users, for example in 2017 98% of Facebook's revenue was from the advertising services (Statista, 2018). Especially in the case of the Facebook the advertising services the company offers are highly advanced and offer superior targeting, personalization and performance measure features compared to any offline advertising channel making it very influential (e.g. McDermott 2014, Hanna et al, 2011).

Also, previously marketing efforts on social media like Facebook have been considered as a one slice of a broad selection of media channels available for companies, but as this case company proves, nowadays it is possible to almost totally rely on social media as sole channel for marketing activities.

2.3. Audience Targeting on Facebook

With more than a billion daily users Facebook has been able to collect a massive amount of behavioral data about the users of the platform (e.g. Tucker, 2014). In addition to the behavior on the Facebook, many other websites utilize Facebook's features such as "like" and "share" buttons on their own platforms that track users' website visits across the internet and are able to connect the behavior to the specific Facebook user (e.g. Kantola, 2014). As the Facebook is a clear market leader in social media sector, it is beneficial for the other websites to embed Facebook's pixel, a piece of code that connects website visitors to their Facebook accounts in order to later target these people more effectively with Facebook's advertising services (e.g. Lambrecht & Tucker 2013).

In essence, Facebook has grown to the position in which also businesses are willing to give their information and for example website visitor logs or newsletter subscriber emails to the Facebook so that they get more customizable and effective advertising services from Facebook (e.g. Lambrecht & Tucker 2013).

With the wide range of types of data Facebook has about its users it can offer very accurate and effective advertising services for the companies. For example, the Facebook pixel allows company to for example target people who have visited their webstore, viewed certain products or viewed company's content on Facebook or Instagram which is also owned by Facebook.

In addition to engagement-related, online behavioral data, offline behavioral data such as age, sex, location, personal interests or hobbies are also possible targeting variables on Facebook which help advertisers to more accurately differentiate and target their intended audience.

Compared to the usage of traditional offline channels, Facebook's targeting tools have revolutionized advertising industry quite thoroughly because of its superior easiness and effectiveness (e.g. Kumar et al, 2015). Overall it is way cheaper solutions for the companies to reach their specific target groups and plan the advertising efforts based on the target audience more in detail than ever before (Hanna et al, 2011).

2.4. Personalization of the Content

As mentioned above, Facebook's targeting tools have made it easy to target very specific target groups based on wide range of characteristics. This leads to the fact that unlike ever before, companies can have very different messages for different target groups as the Facebook advertisements are only shown for the specific target group. This has led to more personalized marketing content that can be tailored specifically to each target group. Also, different kind of marketing messages can be utilized effectively for different purposes like improving brand awareness, engaging the audience or driving sales.

Tailoring the marketing messages specifically for different segments naturally improves the effectiveness of the advertising as the content shown for each possible customer is engaging just for them. (Okazaki & Taylor 2013).

Personalized and customer-oriented marketing messages have been proven to be more appealing to consumers as well as being more effective in creating brand engagement and even sales, especially when the audience has shown interest towards the product category in their online behavior (Lambrecht & Tucker, 2013).

Lastly, unlike to what for example Goldsmith and Freiden (2004) described in the early 2000s, the customization and personalization of marketing efforts is no longer expensive and resource-heavy approach that's only available for well-established companies. Thanks to companies like Facebook and Google, the personalization of advertisements based on people's online behavior has become industry standard, making it affordable and lucrative for even small and up-and-coming firms to have very deeply personalized and customer-oriented marketing activities (e.g. Lambrecht & Tucker 2013).

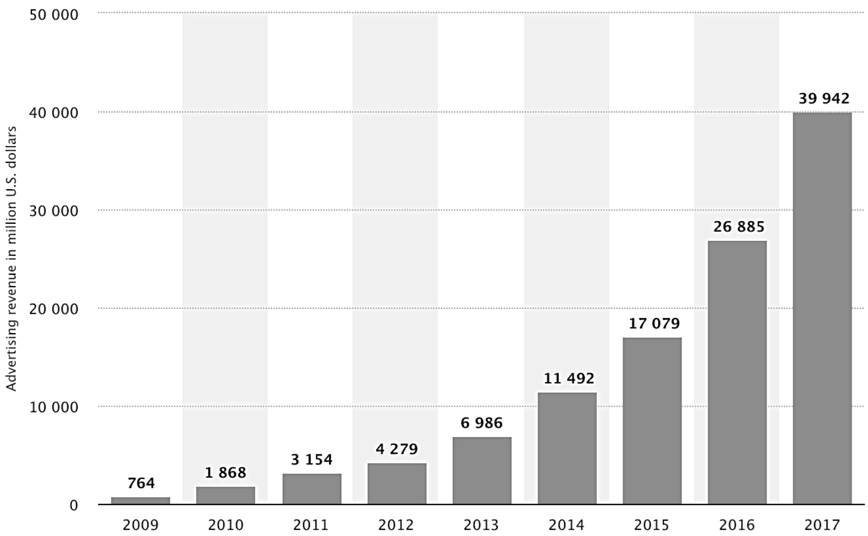
2.5. Performance Tracking of Advertisements on Facebook

In addition to the targeting and personalization tools, Facebook collects comprehensive data about the performance of the advertising campaign on the platform (Tucker, 2014). By creating marketing campaigns, advertisers can easily monitor the performance of their advertisements, test different messages for different target groups and so on. Facebook allows advertisers to truly track the performance of their campaigns and even draw connections between advertisements seen on Facebook and sales on companies' webstores (Kantola, 2014, Kumar et al., 2015). Overall Facebook has made measuring the return on investment in marketing more realistic than ever before. Compared to traditional marketing channels like for example newspaper or TV advertisements where things like the reach, actual impression created and actions like engagement with the brand where highly speculative and uncertain, Facebook gives advertisers actual numbers on these things making the performance evaluation way more realistic, helping with budget allocation and targeting decisions Kumar et al., 2015).

All in all, when combining all these differentiating factors with relatively low cost of Facebook advertising (e.g. Dehghani & Tumer, 2015), Facebook offers one of the most sophisticated and effective advertising channels available and it is understandable that many companies want to utilize these services (Mochon et al., 2013, Kumar et al., 2015). This can also be seen from the figure 1, illustrating Facebook's revenue from the advertising services, which has been growing rapidly over the past ten years. It is clear that the growing userbase and Facebook's status as a market leader has also made it more lucrative service for advertisers (e.g. Mochon et al., 2013).

Figure 1
Facebook's advertising Revenue 2009-2017 in millions of U.S. dollars

(Statista, 2018)



Also, in order to promote the advertising services offered, Facebook has changed its algorithms in favor of the people over companies (Zuckerberg, 2018), meaning that it is harder for the companies to achieve organic visibility in the platform so to reach their audience, they have to use the Facebook advertising services and pay for the visibility (Kumar et al., 2015, Loten, Janofsky & Albergotti, 2014). This will further increase the competition for the attention of the Facebook users and demand companies advertising on the Facebook to have more strategic approach for their marketing campaigns and evaluating the performance of them.

2.6. The Value of Social Media Engagement with the Brand

Currently the main benefits of the company's presence on social media come from the brand engagement (Kumar et al, 2015), as companies are still finding effective ways to convert the visibility and engagement into sales (e.g. Mochon et al., 2017).

While the monetary or the actual sales value of for example Facebook likes is still unclear, it has been proven that the customers who are engaged with the company on social media with for example likes and comments to the company's posts are a valuable asset to the company and the relationship and engagement with these customers need to be fostered and developed carefully (e.g. Sanne & Wiese, 2018 and Kumar et al., 2015).

It has also been shown that the customers who are the engaged with the brand on social media platforms also have higher brand loyalty (Campbell and Keller, 2003, Palmatier et al., 2006) and higher customer lifetime value and profitability for the company (Kumar et al., 2015).

As achieving customer engagement seems to be the most crucial element in succeeding in social media marketing (e.g. Mochon et al., 2017), companies need to put significant effort into creating engaging content for all of the customer segments they wish to target. With the help of Facebook's advertising services, it is easy to reach different customer segments with different content and marketing messages making the company's social media presence seem coherent for the customers while there can be rather significant differences in the content customers see (e.g. Meyer et al. 2011). However, even though social media offers a possibility to differentiate the marketing messages for different audience segments, companies should keep the underlying company brand in mind and still communicate coherent brand across the segments (Matra & Keller, 2016).

As the most engaged customers are a valuable asset for the company, the social media presence of the company is not just about communicating company's messages to the customers, the social media actions are part of the customer relationship management and more customer-centric approach into the relationship between the company and its customers (e.g. Kumar et al., 2011).

While the existence of social media platforms and the fast flow of information it has made possible, the organic word of mouth content that people create on these platforms is increasingly important for consumers as they trust people over the companies themselves as well as they look for information about company or its products. Word of mouth is also important for the companies as consumers perceive it more reliable and it is more effective in terms of influencing people's brand perceptions (e.g. Baxendale et al., 2015) and purchase intention (Deghani & Tumer, 2015).

Positive word of mouth and engaging these core customers is crucial especially for the such small and up and coming companies as these people will act as opinion leaders online and lead the larger audience to interact with the brand (Baxendale et al., 2015).

2.7. Effect of Repetitive Marketing Messages

Previous research like Dehghani and Tumer (2015) show that there is clear correlation between consumer's exposure to the social media advertising and the increase in brand consideration and purchase intention. In the light of these findings, Social media advertising seems very lucrative for the companies that want to reach the customer segments that are heavy users of the social media and affect their purchase behavior.

Additionally, Kumar et al. (2015) found that firm-generated content on social media indeed affects consumer's spending behavior and profitability of the firm-customer relationship. Kumar et al. also note that these effects are greater the longer the firm-customer relationship has been, proving that the social media engagement and online customer relationship management are important tools for improving brand loyalty and the profitability of these most engaged customers.

Repetitive marketing messages or exposures to the brand, no matter the touchpoint increase the customers' brand perception as well as bran consideration, i.e. how willing are they to buy products or services of this specific brand (Baxendale et al., 2015). This lines up with other research on advertising like Kumar et al. (2015) that online advertising actually changes people's behavior and develop the firm-customer relationships.

Traditionally repetitive marketing messages has been considered as an effective way to increase brand awareness among consumers, especially if the company manages to reach people through multiple channels or touchpoints as in the study by Baxendale et al. (2015).

However, Despite the fact that Baxendale et al. (2015) and others found repetitive marketing messages effective in changing people's perceptions and attitudes toward brand, Chatterjee et al. (2003) found that the effect of repetitive exposure to the online banner advertisements is negative, so even though there might be initial positive response, repetitiveness counters the effect and the consumers' brand perception turns negative actually decreasing the brand consideration.

It is worth noting that the Chatterjee et al. (2003) study is rather old and the online advertisement tools have improved drastically since their study. It is also worth noting that they studied banner ads on websites where the advertisement is less integrated to the rest of website than for example on Facebook where the advertisements blend into the stream of people's newsfeed very well. Another attribute that Facebook advertising possesses but Chatterjee et al. did not or could not at the time to examine is the personalized content and how it affects the effectiveness of repetitive marketing messages. As discussed earlier, on Facebook it is easy to personalize the marketing material to the interests of the audience. For example, company can advertise certain products to the people who have viewed them on the company's website or webstore thus making the marketing messages fa more relevant to the customer. As mentioned above, personalized, relevant marketing messages are more effective than generic ones (e.g. Okazaki & Taylor, 2013), so it is likely that the findings of Chatterjee et al. (2003) cannot be applied to modern social media advertising as such.

Additionally, especially on Facebook the repetitive advertisements are largely based on the previous actions of the user and other similar people (Lambrecht & Tucker, 2013), so it is likely that people have shown interest on the brand or the product or service category before, which further improves the relevance of the advertisements for them, making engagement, i.e. likes and clicks ever more likely.

2.8. Retargeting

Retargeting is often misunderstood as being a synonym to remarketing, which refers to more traditional strategy of using the information gathered from customers' previous purchases from the company to advertise them so that they would buy again from the same company. Retargeting is a more recent addition to the tactics that marketers use, and it is mainly based on the information gathered from the overall online activity of the user (Kantola, 2014, Lambrecht & Tucker, 2013). As discussed before, Facebook offers marketers easy-to-use tools for connecting people's Facebook profiles to their online behavior, like visiting company's website or webstore and then targeting advertisements on the service based on these interactions with the brand. This way for example people who have visited the webstore and viewed certain products during previous days can be targeted and this way remind them about the product (Lambrecht & Tucker, 2013).

For example, Ansari and Mela (2003) have found that personalized advertisements attract people's attention better than generic advertisements. Customization of the marketing messages based on previous actions also increases the relevance of the advertisements for the customers, being more effective. It has also been proven by multiple case studies that retargeting people who have shown interest towards brand or products improves people's brand perceptions and brand consideration (Baxendale et al., 2015). In addition to that, retargeting results in improve in the click-through rate, conversion rate and conversion value (Insidefacebook.com, 2014). Due to the increase in these performance metrics, these customer segments are the most likely to convert and with higher value, so companies should track these people and target them. Also, as mentioned before, these customers are also the engaged customers who will if their firm-customer relationship is managed well over time, become the most valuable customers for the company in terms of the customer-lifetime value, but also in regards of the content engagement and word of mouth, both online and offline.

Retargeting is closely tied with the effectiveness of repetitive marketing messages, as the purpose of the retargeting is to remind people about the brand and build stronger firm-consumer relationship through relevant and personalized content. As mentioned in the previous section, repetitive marketing messages can be effective tool to build brand awareness and improve brand consideration, but also repetitive marketing messages with no personalized or relevant content can be irritative and lead cause negative effect on brand consideration. As retargeting, especially on Facebook is usually done by reminding people about the products they have looked at (Lambrecht & Tucker, 2013), or even offer sales on them, the relevance of the advertisements for the customer is higher and thus the negative effects of the repetitive marketing messages that Chatterjee et al. (2003) describe are unlikely to occur (Baxendale et al., 2015, Kumar et al., 2015).

Also, the people who have already interacted with the brand by for example visiting the company's website or webstore are already for some degree engaged with the brand, so retargeting to these consumers is also very effective way to improve the firm-customer relationship. So, whereas traditional repetitive marketing messages aimed to improve brand awareness (Chatterjee et al., 2003), modern online advertising utilizes retargeting as a way to build firm-customer relationship on an individual customer level by utilizing wide range of information points to create relevant and personalized messages. For example, reminding people about product views or adds to cart on webstore is an easy way to make the advertisement material very personalized.

In case of the webstore visits and product views, very common tool is to use sale as a tool to make people act based on the retargeted advertisement. This tactic first of all affects very positively firm-customer relationship as the customer gets the feeling that the company values the customer and is willing to take actions to ensure the customer satisfaction. Also, already in 2004 Anderson and Simester found that customers acquired through sales have higher customer lifetime value. This was explained by higher probability of repeat purchases that even out and even exceed the original sale. However, it is worth noting that this study didn't consider online environment, but the findings should be still somewhat generalizable as the webstores and online advertisement have largely taken the place of mail catalogs and offline sale coupons.

Overall the retargeting is very relevant topic for this research, as the products of company X are higher-end fashion accessories and consumers are not likely to buy the products on their first visit to the company's website and webstore. Especially with such narrow selection of marketing channels, understanding the customers' reaction to company's marketing material becomes extremely crucial for growing sustainable business.

2.9. Returning Customers

As company X primarily aims to reach fresh audience on Facebook and establish the first brand connection with people, analyzing the behavior of customers returning to the website is also relevant, as they are most likely to purchase products. Also, analyzing whether there's difference in behavior between returning customers through retargeting and customers coming to the website on their own is important in order to understand whether the current retargeting advertisement works and engages its audience successfully.

These people can be considered to be the group with strongest engagement with the brand as these people are returning on the company's website on their own, without further marketing efforts bringing them back. This lines up with Kukar-Kinney and Close (2009), who argued that customers use webstore browsing and cart-adding as a way to entertain themselves or to plan their future purchases. In this light the fact that customers who have visited the webstore previously come back on their own represents stronger engagement with the brand than people who receive advertisements and then come back.

Additionally, people who seek to interact with the brand without incentive from the brand have higher level of brand engagement compared to the people who are targeted with advertising without their consent or prior interest towards the brand (Campbell and Keller, 2003, Palmatier et al., 2006). So, for the companies operating in the online environment, people returning to the website or webstore without the need for further marketing activities are likely the most valuable customers as they seek to engage

with the brand showing the initiative.

2.10. Overview of Most Relevant Literature

The figure 2 sums up the most relevant literature on Facebook advertising and repetitive marketing. As can be seen studies that truly manages to combine analytics from social media engagement and actual sales of these individuals are very rare, Kumar et al. (2015) and Lambrecht & Tucker (2013) being the only ones presented here. Furthermore, from these two, Kumar et al. focuses on other communication channels as well and doesn't consider retargeting. It is clear that obtaining social media advertisement data and actually proving its effectiveness in practice is difficult and thus many of the studies presented on the table two rely on questionnaires and mock up -situations or like Brettel et al. (2015) take the social media engagement as a whole and compares it to sales figures.

It is safe to say that it is crucial to study the relationship between social media advertising and purchasing behavior in greater detail as there seems to be significant gap in the current research. Additionally, there seems to be rather contradictory findings on the effectiveness of repetitive marketing messages (Campbell & Keller, 2003, Lambrecht & Tucker, 2013, Baxendale et al., 2015, Chatterjee et al., 2003). Another thing not well studied is how the webstore behavior differs between the new and retargeted audiences who end up clicking the advertisements, enabling this study to fill yet another gap in existing literature.

Figure 2
Overview of the Most Relevant Literature

Writers	Research Questions	Data Used	Theories Used to Form the Study	Findings
Kumar et al. 2015	What is the effect of Firm Generated content on customer spending and cross-buying behavior? What is the effect of social media engagement on customer purchasing behavior?	Data set from a large specialty retailer that sells wine and spirits. Combining survey results to social media and newsletter follower data in order to analyze their effects on offline purchasing behavior	Long brand relationship leads to more positive attitude (Campbell and Keller 2003), Social media interaciton improves brand attitude (Naylor, Lamberton, and West 2012), FGC has positive effect to customer profitability Danaher and Dagger (2013)	Social media has synergy benefits when used with other media, FGC on social media is more effective than on other channels, improving purchasing and firm-customer relationship especially when relationship is longer
Brettel et al. 2015	Which stimuli in a social network drive short-term sales? What is the long-term impact of Facebook stimuli on sales?	German ecommerce retailer, 12 month period, Facebook stream impressions, page views, likes, contributions (comments, content), how the Social media as a whole affects daily sales	Facebook engagement generates sales (Cruz and Mendelsohn, 2010), Brand engagement builds brand relationship and leads to purchasing (Vakratsas and Ambler, 1999)	Engagement with brand and its content on Facebook improves sales especially in long run, Involuntary exposure to the brand negatively impacts sales
Dehghani & Tumer (2015)	How advertising on Facebook affects consumers' purchase intention?	Questionnaire about the effectiveness of and attitudes towards Facebook advertising	Facebook is used to enhance brand image (Kaplan & Haenlein, 2010, Chu, 2011), Social media is important place for finding content that affects purchase intention (Hoy & Milne, 2010)	Facebook content aimed for maximized engagement is effective tool for CRM, Facebook engagement indicates higher purchase intention
Campbell and Keller, 2003	How repetitive advertising effects differ between unknown (involuntary exposure) and known (voluntary exposure) brands?	two different lab studies with n over 100 to analyze effects of repetitive known and unknown brand exposure across different sources	Berlyne (1970) repetitive marketing messages from unknown brand have positive impact making the brnad more known until certain point after which starts to have negative effect on brand consideration	repetitive ads from unfamiliar brands wear out quicker resulting in negative effects, previously known brands can have more repetitiveness while maintaining the ad effectiveness and positivity towards the brand

Baxendale et al., 2015	How different touchpoints and their frequency and positivity affect brand consideration	Real-time experience tracking on touchpoints, frequency and brand cosideration, one week, three product categories with differnet levels of involvement needed	Frequency may impact brand attitudes by increasing brand awareness (Yaveroglu and Donthu 2008). Repetition can also improve learning (Goh, Hui, and Png 2011).	Frequency and positivity affect brand considerations, positivity towards touchpoint has larger effect, but it's likely that low recall diminishes the effect rather quickly
Chatterjee et al. (2003)	How repetitive exposure to the online advertisments affect the performance of the advertisement?	Data on website banner ad exposures and clicks, two advertisers, 7.5 month period,	Each exposure is less effective than previous (Buchanan and Morrison 1988) or repetitiveness has a positive effect until certain point after which it becomes negative (Berlyne, 1970)	Repetitive exposure to ads has negative and nonlinear effect, repetitive exposure however predicts clicking in the future sessions
Lambrecht & Tucker, 2013	Does personalized (dynamic) ads overperform generic ones when ads are show on external sites?	Generic and dynamic retageted ads for consumers who visited the Travel company website on other websites, clicks and purchases based on the exposure to the differnet ads	Personalized dynamic ads perform better (Hargrave 2011; Hunter et al. 2010), Retargeted, dynamic ads work better when consumers know what they want (Lee et al., 2010)	Generic retargeting works better, but when users start product search and comparison, dynamic ads start to perform better

2.11. Hypotheses

Based on the existing literature presented in this chapter, following hypotheses are drawn to guide the analytical part of this study applying the theory to the case company:

Hypothesis 1: *Previous engagement with the brand leads to higher engagement with the Facebook advertisements (liking, commenting and clicking).*

To understand the Hypothesis 1 as well as the other further on, it is important to understand what is meant by engagement with the Facebook advertising. As Kumar & Bezawada (2014) defined what they called customer participation with the brand, there are two parts to that; customer interaction and customer engagement. Customer interaction meaning how audience reacts to firm-generated content, such as advertisements, they come across on social media and customer engagement which was about what kind of content audience creates about the brand online, meaning reviews, comments, posts and so on. For this hypothesis, interaction part of Kumar & Bezawada's definition will be used as a definition of engagement as paid advertisements on Facebook are something the audience cannot choose to or not to see and will have to react without much preparation (comparing to for example writing a review about the company). Additionally, audience cannot later on find the advertisement they saw before as they are auctioned individually to each user's Facebook feed. Due to the reactiveness in the way audience comes across the advertisements, comments are also considered as a part of Kumar & Bezawada's interaction in this case. However, for the sake of simplicity and coherence with other literature, customer engagement will be used as a broader topic in similar way that Kumar & Bezawada used customer participation.
Sanne & Wise (2018) found in their study that existing attitudes towards the brand in question is the strongest indicator of engagement with firm-generated content. They found that the more positive pre-existing attitude based on the previous encounters the customers have the more likely they are to engage with company's content on social media. They also found that the engagement of other people encouraged further engagement, further increasing the engagement rates. If a customer has already interacted with the brand on social media or on website and started to build up a relationship with the brand, they are more likely to engage again feeding the encouragement to engage among others. Over time the customer engagement leads to higher customer loyalty (Campbell and Keller, 2003, Palmatier et al., 2006), Which can be considered even more positive brand attitude (e.g. Dehghani & Tumer (2015) leading to more engagement with the content (Sanne & Wise, 2018, Dehghani & Tumer (2015)). Additionally, Brettel et al. (2015) found that when exposure to the brand is involuntary (like first-time Facebook advertisements) effect on brand

consideration is significantly negative, whereas if the exposure is voluntary, for example as a result of previous engagement, the effect on brand attitude is positive (also, Kumar et al., 2015) feeding the behavioral intent to engage (Sanne & Wise, 2018) even more.

Hypothesis 2: *The deeper the engagement with the brand, the more valuable the customers are in terms of the revenue.*

For the companies, the presence on social media is largely marketing-driven and social media platforms can be seen as a modern extension of marketing channels available for the company (Kumar et al., 2015). However, unlike other, more traditional channels, the two-way communication made possible by these social media platforms makes them unique channels that allow more equity-building aimed activities that focus on managing brand image and creating and nurturing customer relationships even on personal level with the customers (Kumar et al., 2015). Similarly to cultivating future brand engagement, customer-firm relationships are cultivated and managed in order to maximize customer's lifetime value for the brand (Kumar et al., 2015). In social media setting the value customer has, might also be related to being sort of online spokesperson for the brand as described previously (e.g. Sanne & Wise, 2018), but for this hypothesis, only monetary value of actual purchases will be considered as a part of customer lifetime value. It is widely agreed among researchers that
As described above, exposure and engagement with the brand and its content shapes audience's perception towards the brand (Sanne & Wise, 2018). This positive shift leads to more willingness to further engage with the brand and in this way create and deepen the firm-customer relationship (Sanne & Wise, 2018). Over time engagement with the brand leads more positive brand perception and improved purchased intention towards that brand (Sanne & Wise, 2018, Kumar et al., 2015). Further on, brand engagement and firm-customer relationship lead to higher brand loyalty and preference over other products (Campbell & Keller, 2003) and as customer prefers the brand over others the lifetime value of the customer's revenue to the company becomes higher, thanks to the firm-customer relationship and ongoing customer engagement (Kumar et al., 2015).
Additionally, Brettel et al. (2015) as well as Dehghani & Tumer (2015) found that engagement with the brand specifically on Facebook improves the sales revenue of the company, positively affecting the customer lifetime value. So, there is rather clear consensus among the past studies that engagement is a strong predictor of purchase intention and higher sales revenue. Additionally, for example Villaneuva et al. (2007) proposed that when targeting audience with advertisements, the customers attracted and acquired with them usually generate more short-term revenue, while

customers acquired through for example word-of-mouth, which is more complex and heavily engagement-relying channel, are more valuable in long term. This brings further support for the Hypothesis 2 as the core idea is to study whether previous engagement and sort of depth of it affects the customer lifetime value significantly.

Hypothesis 3: *More time spent on the website engaging with the brand leads to higher conversion rates and revenue.*

Continuing the idea that engagement has a positive effect on customers' purchase intention (Kumar et al., 2015, Campbell & Keller, 2003) it is important to try to measure the depth of brand engagement customers have. One, quite obvious way to do this is to measure the time they spend on exploring the company's website and webstore. It is rather clear that if the customer is interested in the brand, they are more willing to spend time and consume the content of the brand (Sanne & Wise, 2018). Based on for example the Sanne and Wise's (2018) idea of brand attitude being shaped by engagement over time, more time spent on the website should lead on deeper and stronger engagement with the brand leading into positivity towards brand and its products (Campbell & Keller, 2003) and finally to improved purchase intention (Kumar et al., 2015, Campbell & Keller, 2003). Additionally, Brettel et al. (2015) found that engagement with firm-generated content on Facebook led to increase in sales, so it would be interesting to analyze whether the engagement with the website content has similar effect as the audience clicking through the Facebook advertisement to explore the website have already sort of converted and most definitely presented interest and positivity towards the brand (Sanne & Wise, 2018, Kumar & Bezawada, 2014). So as social media engagement has been proven to have effect on purchase intention and sales revenue (Brettel et al., 2015, Kumar et al., 2015, Campbell & Keller, 2003, Villanueva et al., 2007) it is reasonable to expect that the engagement with the website content should have similar effects. The best way to study whether this correlation exists, is to study whether the time spent on the website has an effect on conversion rate or revenue per user.

Hypothesis 4: *Facebook engagement (likes and comments) have positive effect on webstore revenue and conversion rate.*

Hypothesis 4 is drawing from the Hypotheses 1 and 2 and underlying theories and previous findings on how engagement feeds engagement on Facebook (Sanne & Wise, 2018) as well as how previous engagement with the brand, especially on Facebook, has a long-term effect on purchase intention

(Baxendale et al., 2015) and improving sales revenue (Brettel et al., 2015, Dehghani & Tumer, 2015 and Kumar et al., 2015) and overall customer lifetime value (Kumar et al., 2015). Based on these findings, there should be cross-platform correlation between Facebook engagement (liking and commenting) and sales revenue as well as conversion rate. In addition to other researchers landing on similar conclusions, the main source for this hypothesis is still Brettel et al. (2015) who, by using different research methods, found this clear correlation in the behavior of customers they studied. When combining their crystal-clear finding with the consensus among researchers that engagement indeed fosters engagement as well as sales, this sort of cross-platform analysis on how the brand engagement of the audience presents itself is really interesting. In the sense the goal is to study whether the findings of study by Brettel et al. (2015) and framework they presented is applicable for this case company or Facebook advertising in general.

3. METHODOLOGY

As mentioned before, Facebook advertising is considered very well targeted and utilizes personalization to the single customer level. Because of the sophisticated marketing tools and the fact that the Facebook is clear market leader among the social media platforms (especially when considering Instagram as a part of it), Facebook algorithms can be considered extremely effective (e.g. Mochon et al., 2013). So, when targeting for example people interested in watches, Facebook makes sure that the people who see the advertisements are indeed interested in to the products. Because of that, it is rather difficult (and not beneficial for the business) to create advertisements that reach truly neutral audience. In this sense Facebook advertising is almost too effective. Additionally, the unique, auction-based advertising makes it even more difficult to know who actually sees the advertisements. Because of that, this study relies completely on the anonymized data that Facebook generates from the advertisement campaigns. Due to the problems this anonymity poses, it has to be assumed that all people seeing the advertisements are similarly interested into the products because Facebook algorithm showed the advertisements to them. Additionally, the anonymity of data from Facebook advertising drastically reduces the possibility to analyze and study other variables possibly influencing the customer behavior.

In addition to that, there are no extensive studies conducted on the whole customer journey from online advertising on social media platforms to the actual website behavior and eventual purchasing behavior. That combined with the inconclusive research on the effectiveness of repetitive marketing messages, it is impossible to format useful and overarching research questions. That is why it is safer to settle on explorative study that tries to shine light on the role of brand engagement and repetitive marketing messages might have on people's online shopping behavior.

Company X also runs many advertisement campaigns with overlapping audiences each day, so the following audience grouping is the only way to establish and study differences between the people who are targeted by advertisement and visit the website of the company.

3.1. Audience Groups

The website visitors can be divided into three groups based on their engagement with the company;

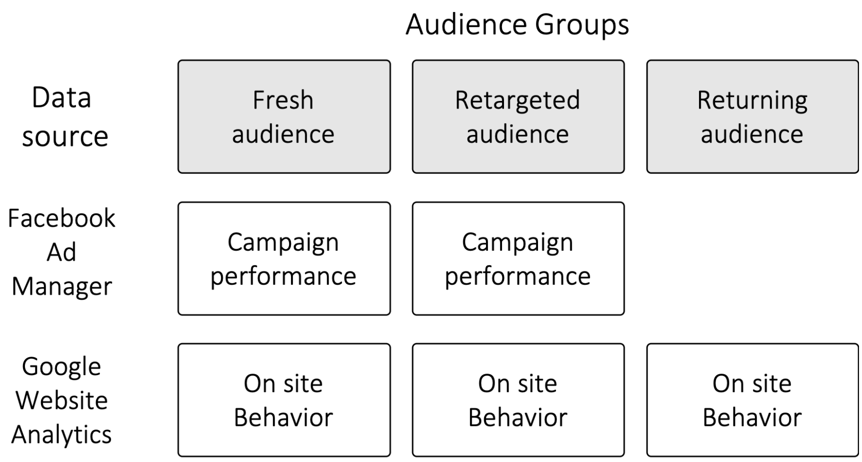
1. Fresh audience
2. Retargeted audience
3. Returning customers

The first group is so called fresh audience who have no previous connection to the brand and are targeted by Facebook advertising. The second group is consisted of people retargeted with Facebook advertising. These people have different level of previous exposure to the brand, ranging from social media engagement to shopping cart abandonment on the company webstore. Even though the Facebook advertisement campaigns are targeted so that there shouldn't be overlap between the fresh and retargeted audience, it is impossible to be absolutely certain that the no one in the fresh audience hasn't had any encounter with the brand. However, for the sake this research, it is assumed. The third audience segment is the people who have previous contact with the company's website and return to it themselves via search engine such as Google or straight navigating to it. So, in essence these people come back to the website on their own unlike the second segment who have been reminded about the brand and the website by Facebook advertisement. As mentioned before, the group three can be considered to be the group with strongest engagement with the brand as these people are returning on the company's website on their own, without further marketing efforts bringing them (Kukar-Kinney & Close, 2009).

3.2. Data collection

Figure 3

Illustration of Data Collection and Sources



As the main goal of this study is to uncover the possible differences in the behavior of three audience groups; 1) The fresh audience, 2) The retargeted audience and 3) The organic returning customers. As the first and the second group are targeted by Facebook advertising, data from Facebook advertising campaigns will be used to find out if there are significant differences among the groups.

Furthermore, Google analytics data drawn from company's website will be utilized to analyze the on-site behavior and possible differences between these groups. Naturally comparing the other groups to group 3 will be solely based on the website analytics data as there's no Facebook data of this group's behavior.

On the Facebook side the reaction to the advertisements will be analyzed by comparing the behavior of group 1 to group 2. The data points to be analyzed are post engagement and outbound clicks. Post engagement illustrates how many people have engaged with the advertisement. In the case of Facebook, this means liking the advertisement or commenting it. The number of outbound clicks then again tells how many people have clicked a link on the advertisement that leads them to a website that is not part of the Facebook properties. In this case it means links that lead to the company's webstore. It is crucial to use outbound clicks as other clicks might include for example clicking the advertiser's name which leads to company's Facebook site. This way the people clicking the link in the advertisement can be identified and matched with the data from the webstore.

Another crucial thing is to use ratios with impressions as the audience sizes vary a lot. On average advertisements targeted to the fresh audience achieved 77 238 impressions per day while retargeting advertisements reached on average 5746 impressions per day. Additionally, the group three consisted on average 213 website users per day making it even smaller group. This means using for example the ratio of people who have clicked the advertisement compared to the total number of people who have seen the advertisement. This way very different sized audiences can be compared. It is worth noting that despite the groups seem disproportionate for comparison, using ratios makes the groups comparable.

The figure 3 above illustrates the collection of the data. Due to the limitations in company's data collection and ability to combine the data points from different sources, 62-day time period starting Monday, the 10th of September 2018 and ending on Saturday, the 10th of November 2018 was chosen for this study. The Facebook advertising data is obtained directly from the company X's Facebook advertising account. The data was exported from the Facebook account and then cleaned and organized on Excel. The divide between the advertisements targeting fresh and retargeted audiences was made based on the ad set names that identify the target groups. Then, the data was formatted based on this retargeting variable using pivot-table. As Facebook data is in absolute numbers, engagement ratio and click ratio had to be calculated by dividing the absolute numbers by the number of impressions (i.e. how many people saw the advertisement)

The figure 4 below illustrates the descriptive statistics for the Fresh and Retargeted audiences. As there is no Facebook data for the Returning audience, these two groups need to be analyzed separately to study the effects of the Facebook advertising and engagement it creates.

Figure 4

Descriptive Statistics

Fresh Audience and Retargeted Audience

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Pages per session average	124	1.7774175090	5.78571428571	3.12405260624	.773059355037	.598
Revenue/users	124	.000	9.19485714285	.508611447722	1.30463592166	1.702
Conversion rate	124	.000	.05714285714	.003583380662	.00822117142	.000
Clicks/impressions	124	.00283784655	.02124645892	.008629220828	.00400362054	.000
Engagement/impressions	124	.00695226999	.043439911797	.020857616838	.006398501518	.000

In the Google Analytics side of the things the behavior of these groups can be analyzed and compared further in the marketing funnel. The new and returning users can be separated and the users coming from the Facebook can be identified based on the source medium they used. For the group three, the returning customers, the organic channels such as organic search and direct traffic were used as the identifying mediums. Also, the paid search has to be taken into account as people rarely remember the exact website addresses and when searching the company on the Google, the paid links appear on the top of the search results making otherwise organic traffic appear as paid.

What comes to the actual data obtained from the website analytics, revenue of the website purchases and average number of pages per website visitor are used to compare the behavior of different customer groups. The data is also daily, so organizing it to match with Facebook data. Also, day to day differences in the performance of Facebook advertisement campaigns won't affect the results significantly. Combining the revenue with the number of people clicking the Facebook ad we can calculate the revenue per user -values that are better for comparison as the sizes of these groups differ quite a lot. Additionally, the number of transactions form each group can be used to calculate the conversion rates for each customer group.

These variables were chosen as the revenue per user (measured as an average euros per user) and conversion rate (measured as a percentage of users who purchased something of the total number of users) as a are widely used ecommerce metrics and are acceptable metrics for the success. In terms of the Facebook metrics, click rate and engagement rate are also industry standards for measuring the performance of the advertisement campaigns on the platform. Additionally, like many companies operating solely via webstore, the advertising campaigns of company X promote the website heavily and the main goal of the advertisements is to direct users to the company's website. The average

pages per session -variable was chosen to further illuminate the differences in on website behavior as it rather clearly illustrates the interest the user has towards the brand and its products.
The website behavior data was similarly exported from the Google Analytics account of Company X by selecting the variables needed and as mentioned before, widely used to measure the webstore performance. Then the data was combined to the Facebook data on Excel by matching the dates and user groups. The group 3, returning audience was also added in order to have better understanding on the differences between groups and actually have something to compare the effect of Facebook advertising. The figure 5 below shows the descriptive statistics of the website analytics for all the audience groups.

Figure 5
Descriptive Statistics
Fresh Audience, Retargeted Audience, Returning Audience

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Pages per session average	186	.000	7.042590673575	2.947011650994	1.194568006600	1.427
Revenue/users	186	.000	9.194857142857	1.375053921979	1.672434205458	2.797
Conversion rate	186	.000	.0571428571428	.0072338950689	.010251005172	.000

3.3 Data Analysis

The analysis of the data is divided into two parts; first, pair-wise t-tests and ANOVA are used to whether there are statistically significant differences in the behavior between the three groups. T test is used to uncover whether the behavior of Retargeted audience differs from Fresh audience (in terms of Facebook and website behavior) and also whether the behavior Retargeted audience differs from Returning audience (regarding on website behavior). Additionally, ANOVA is used to make sure that these three groups are all different from one other. As ANOVA allows comparing the means of more than two groups to each other at once and establishing the statistical differences between all of them, it has to be used to validate the differences found with pair-wise t-test. Without conducting ANOVA and relying only on t-tests, there would be chance that only one of the groups would statistically significantly differ from the two others while the means of the two would be statistically similar i.e.

there would not be statistically significant difference between them even though they differ from the third group.

As there is no Facebook data from Returning audience, t test is reliable and easy way to compare the groups two at the time. In addition to that, regression analyses are used to analyze how the behavioral variables might affect and explain changes in each other.

4. FINDINGS OF THE DATA ANALYSIS

In this section the results of the data analyses are presented, and the results are discussed to create understanding on what kind of difference are between the audience groups and how the different variables from Facebook and on-site behavior explain the business metrics i.e. the average revenue per customer and conversion rate.

To analyze whether the behavior of fresh audience, retargeted audience and returning customers actually differs from one other, t-tests and ANOVA-analysis are needed. The t-tests show the statistically significant differences between the two groups. To analyze all the variables, all groups need to be tested against each other. Additionally, ANOVA-analysis helps to confirm the findings of the t-tests by analyzing all the groups against each other at once and establishes whether all the groups are actually statistically significantly different from one other.

As there is no Facebook-data for group 3, groups 1 and 2 need to be compared separately in terms of Facebook engagement and advertisement clicks. In case of website behavior, all groups can be analyzed at once.

4.1. Fresh Audience and Retargeted Audience – Differences in Facebook Advertising Responses

Figure 6

Engagement per Impressions t test

Fresh Audience and Retargeted Audience

	Fresh Audience	Retargeted Audience
Mean	0,021721477	0,019993757
Variance	0,000028	0,0000529
Observations	62	62
Pooled Variance	0,0000405	
Hypothesized Mean Difference	0	
df	122	
t Stat	1,51123075	
P(T<=t) one-tail	0,066657789	
t Critical one-tail	1,657439499	
P(T<=t) two-tail	0,133315577	
t Critical two-tail	1,979599878	

Figure 7

Clicks per Impressions t test

Fresh Audience and Retargeted Audience

	Fresh Audience	Retargeted Audience
Mean	0,005133768	0,012124673
Variance	0,0000008	0,0000067
Observations	62	62
Pooled Variance	0,00000374	
Hypothesized Mean Difference	0	
df	122	
t Stat	-20,1219272	
P(T<=t) one-tail	0,00	
t Critical one-tail	1,657439499	
P(T<=t) two-tail	0,00	
t Critical two-tail	1,979599878	

The figures 6 and 7 above illustrate the statistical differences between the Fresh audience and Retargeted audience in terms of the responses to the Facebook advertisements. As can be seen from the figure 6, there is no statistically significant difference in the post engagement between the Fresh audience and retargeted audience ($p=0.133333 > 0.05$). This means that when seeing advertisements from the company X on Facebook, they react to the actual post similarly in terms of likes and comments. Additionally, as can be seen from the relatively low means, (Fresh audience: 0.021 and Retargeted audience: 0.019) only around 2% of the people seeing the advertisements react to them by liking the content or the company's Facebook page. This finding suggest that Hypothesis 1 should be rejected at least when considering engagement in terms of liking and commenting on Facebook.

However, as the figure 7 illustrates, there is statistically significant difference between fresh and retargeted audience when it comes to the advertisement clicks ($p=0.00 < 0.05$). The fresh audience has mean clicks per impressions of 0.005 while Retarget audience has mean of 0.012. So, on average retargeted audience is more than twice as likely to click the company's advertisement on Facebook than fresh audience. In this sense, it seems like the previous exposure to the brand makes people more likely to click the advertisement of the brand. This on the other hand supports the Hypothesis 1.

So, even though there's no difference in terms of the likes, fresh and retargeted audience react differently in terms of the clicking the advertisement they see on the Facebook. When it comes to the Hypothesis 1, for now there seems to be data supporting both acceptance and rejection of it. The fact that previous engagement does not seem to affect Facebook engagement supports rejection, while clear difference in click rates supports its acceptance.

4.2. Fresh Audience and Retargeted Audience – Differences in Behavior on the Website

Figure 8

Revenue per User T Test

Fresh Audience and Retargeted Audience

	Fresh Audience	Retargeted Audience
Mean	0,145707745	0,87151515
Variance	0,053338263	3,110998182
Observations	62	62
Pearson Correlation	0,007510074	
Hypothesized Mean Difference	0	
df	61	
t Stat	-3,215853009	
P(T<=t) one-tail	0,001040838	
t Critical one-tail	1,670219484	
P(T<=t) two-tail	0,00	
t Critical two-tail	1,999623585	

Figure 9

Average Pages per Session T Test

Fresh Audience and Retargeted Audience

	Fresh Audience	Retargeted Audience
Mean	3,413629434	2,834475779
Variance	0,50439762	0,530182161
Observations	62	62
Pooled Variance	0,51728989	
Hypothesized Mean Difference	0	
df	122	
t Stat	4,48340171	
P(T<=t) one-tail	8,35443E-06	
t Critical one-tail	1,657439499	
P(T<=t) two-tail	0,00	
t Critical two-tail	1,979599878	

Figure 10

Conversion Rate t test

Fresh Audience and Retargeted Audience

	Fresh Audience	Retargeted Audience
Mean	0,001044255	0,006122506
Variance	0,00000241	0,000120764
Observations	62	62
Pearson Correlation	-0,087268436	
Hypothesized Mean Difference	0	
df	61	
t Stat	-3,560032719	
P(T<=t) one-tail	0,000362763	
t Critical one-tail	1,670219484	
P(T<=t) two-tail	0,000725526	
t Critical two-tail	1,999623585	

As can be seen from the figure 8, there is statistically significant difference between fresh and retargeted audience in terms of the average revenue per user ($p=0.00 < 0.05$). As the figure 6 illustrates, Fresh audience has mean of 0.146 while retargeted audience has mean of 0.872. So, it is

safe to say that the previous exposure to the brand increases the revenue per user significantly when the audience is retargeted with Facebook advertisements. This finding also supports Hypothesis 2 by suggesting that the deeper engagement with. The brand is indeed linked to higher purchase value.
However, as can be seen from the figure 9, the fresh audience shows more interest towards the company's website with mean of 3.41 average pages per session while retargeted audience has mean of 2.83. This difference is also statistically significant ($p=0.00 < 0.05$).
The figure 10 illustrates the statistical difference between the fresh and retargeted audience in terms of the conversion rate. As can be seen from the means, fresh audience has mean conversion rate of 0.001 or 0.1% while retargeted audience has 0.006 or 0.6%. This difference is also statistically significant as can be seen from the figure 8 ($p = 0.0007 < 0.05$). This finding again supports Hypothesis 2 as the audience group with deeper brand engagement has higher conversion rate making them more valuable in terms of purchases.

4.3. Statistical Differences Between Fresh Audience and Retargeted Audience – ANOVA

Figure 11

ANOVA - Fresh audience and Retargetd Audience

		Sum of Squares	df	Mean Square	F	Sig.
Pages per Session Average	Between Groups	10.398	1	10.398	20.101	.000
	Within Groups	63.109	122	.517		
	Total	73.507	123			
Revenue per User	Between Groups	16.331	1	16.331	10.322	.002
	Within Groups	193.025	122	1.582		
	Total	209.355	123			
Conversion Rate	Between Groups	.001	1	.001	12.980	.000
	Within Groups	.008	122	.000		
	Total	.008	123			
Clicks per Impressions	Between Groups	.002	1	.002	404.892	.000
	Within Groups	.000	122	.000		
	Total	.002	123			
Engagement per Impressions	Between Groups	.000	1	.000	2.284	.133
	Within Groups	.005	122	.000		
	Total	.005	123			

The ANOVA analysis table above (figure 11) illustrates the significance of the t-test findings. ANOVA i.e. the analysis on variance is necessary in order to make sure that the differences in the groups are statistically significant and that the results from the t-tests are meaningful. Similar to the t-tests presented before, all of the variables except engagement ratio have statistically significant differences between the fresh and retarget audience. As can be seen from the figure 11, significance numbers (Sig.) are below 0.05 for all the variables (0.000, 0.002, 0.000 and 0.000) but engagement per impression which has Sig = 0.133. So as the t-tests suggested, fresh and retargeted audiences have statistically significant difference in their behavior both on Facebook and on the company's website.

4.4. Retargeted Audience and Returning Audience – Differences on Website Behavior

Figure 12

Revenue per User T Test

Retargeted Audience and Returning Audience

	Retargeted Audience	**Returning Audience**
Mean	0,87151515	2,59292974
Variance	3,110998182	2,931582253
Observations	62	62
Pearson Correlation	0,167979904	
Hypothesized Mean Difference	0	
df	61	
t Stat	-6,044826881	
P(T<=t) one-tail	4,91266E-08	
t Critical one-tail	1,670219484	
P(T<=t) two-tail	0,00	
t Critical two-tail	1,999623585	

Figure 13

Average Pages per Session T Test

Retargeted Audience and Returning Audience

	Retargeted Audience	**Returning Audience**
Mean	2,834475779	3,10793887
Variance	0,530182161	0,472585045
Observations	62	62
Pooled Variance	0,501383603	
Hypothesized Mean Difference	0	
df	122	
t Stat	-2,150277464	
P(T<=t) one-tail	0,016753103	
t Critical one-tail	1,657439499	
P(T<=t) two-tail	0,033506207	

t Critical two-tail	1,979599878

Figure 14

Conversion Rate T Test

Retargeted Audience and Returning Audience

	Retargeted Audience	**Returning Audience**
Mean	0,006122506	0,014534924
Variance	0,000120764	0,000101143
Observations	62	62
Pearson Correlation	-0,111870945	
Hypothesized Mean Difference	0	
df	61	
t Stat	-4,217830829	
P(T<=t) one-tail	4,15589E-05	
t Critical one-tail	1,670219484	
P(T<=t) two-tail	0,00	
t Critical two-tail	1,999623585	

As both retargeted audience from Facebook and audience returning on their own are returning customers of sorts with previous exposure to the brand, it is crucial to analyze whether there are significant behavioral differences between these two groups to further evaluate the success of the Facebook advertising.

The figure 12 illustrates the t-test that compares the differences in mean revenue per user between the retargeted audience and returning audience. As can be seen from the figure 12, there is indeed statistically significant difference between these groups ($p = 0.00 < 0.05$). The mean numbers show that while retargeted audience has mean revenue per user of 0.872, the returning audience has significantly higher 2.593. So, it is clear that the returning audience is much more valuable in terms of the average revenue per user than the retargeted audience.

This finding further supports Hypothesis 2.

In addition to that, the figure 13 above shows that there is also statistically significant difference between the groups in terms of the average pages per session ($p = 0.03 < 0.05$). As can be seen from the figure, returning audience has mean of 3.108 while retargeted audience has mean of 2.834 which is significantly lower.

The figure 14 illustrates the t-test between the groups in terms of conversion rate. The test shows statistically significant difference between the groups ($p = 0.00 < 0.05$) where retargeted audience has mean conversion rate of 0.006 and returning audience has significantly higher 0.014.
This finding supports Hypothesis 2.
So, the returning audience has significantly higher average revenue per user, higher conversion rate as well as higher average pages per session meaning that the returning audience seems to be more valuable in terms of the actual sales as well as in terms of the engagement with the brand as they spend on average more time on the website.
Overall there seems to be rather significant support for Hypothesis 2 as more engaged audience segment, i.e. returning audience seems to be more valuable to the brand in terms of conversion rate and purchase value.

4.5. Fresh Audience and Returning Audience – Differences in Behavior on the Website

Figure 15

Revenue per User T Test

Fresh Audience and Returning Audience

	Fresh Audience	Returning Audience
Mean	0,145707745	2,59292974
Variance	0,053338263	2,931582253
Observations	62	62
Pearson Correlation	-0,109225	
Hypothesized Mean Difference	0	
df	61	
t Stat	-10,995320	
P(T<=t) one-tail	2,08753E-16	
t Critical one-tail	1,670219484	
P(T<=t) two-tail	0,00	
t Critical two-tail	1,999623585	

Figure 16

Average Pages per Session T Test

Fresh Audience and Returning Audience

	Fresh Audience	Returning Audience
Mean	3,413629434	3,10793887
Variance	0,50439762	0,472585045
Observations	62	62
Pearson Correlation	0,784440887	
Hypothesized Mean Difference	0	
df	61	
t Stat	5,240016041	
P(T<=t) one-tail	1,05542E-06	
t Critical one-tail	1,670219484	
P(T<=t) two-tail	0,00	
t Critical two-tail	1,999623585	

Figure 17

Conversion Rate T Test

Fresh Audience and Returning Audience

	Fresh audience	Returning Audience
Mean	0,001044255	0,014534924
Variance	0.0000024	0,000101143
Observations	62	62
Pearson Correlation	-0,055395374	
Hypothesized Mean Difference	0	
df	61	
t Stat	-10,3524131	
P(T<=t) one-tail	2,33075E-15	
t Critical one-tail	1,670219484	
P(T<=t) two-tail	0,00	
t Critical two-tail	1,999623585	

Lastly, the difference between the fresh audience and returning audience needs to be analyzed. As can be seen from the figures 15, 16 and 17, there's statistically significant difference in all variables. Returning audience has significantly higher mean revenue per user 2.593 while fresh audience has 0.146 ($p = 0.00 < 0.05$) (figure 15). The conversion rate (figure 17) is also higher for the returning audience (mean = 0.014) than for fresh audience (mean = 0.001). the difference is also statistically significant (p = 0.00 < 0.05).

These findings are further evidence supporting Hypothesis 2, as the audience segment with deeper brand engagement seems to be more valuable to the company in terms of the conversion rate and average revenue.

Whereas fresh audience has significantly higher average pages per session 3.414, returning audience has a bit lower 3.108 (p = 0.00 < 0.05) (figure 16).

4.6. Statistical Differences between all groups - ANOVA

Figure 18

ANOVA

Fresh Audience, Retargeted Audience and Returning Audience

		Sum of Squares	df	Mean Square	F	Sig.
Pages per session average	Between Groups	22.058	2	11.029	8.342	.000
	Within Groups	241.936	183	1.322		
	Total	263.994	185			
Revenue/users	Between Groups	295.599	2	147.800	121.916	.000
	Within Groups	221.852	183	1.212		
	Total	517.452	185			
Conversion rate	Between Groups	.006	2	.003	38.495	.000
	Within Groups	.014	183	.000		
	Total	.019	185			

As can be seen from the figure 18, all groups differ from one other in terms of the all website behavior variables; average pages per session, revenue per user and conversion rate (Sig. numbers 0.000, 0.000 and 0.000 respectively), meaning that the differences found with the pairwise t tests presented before are reliable and statistically significant and there are real differences between all three groups.

4.7. Regression Models

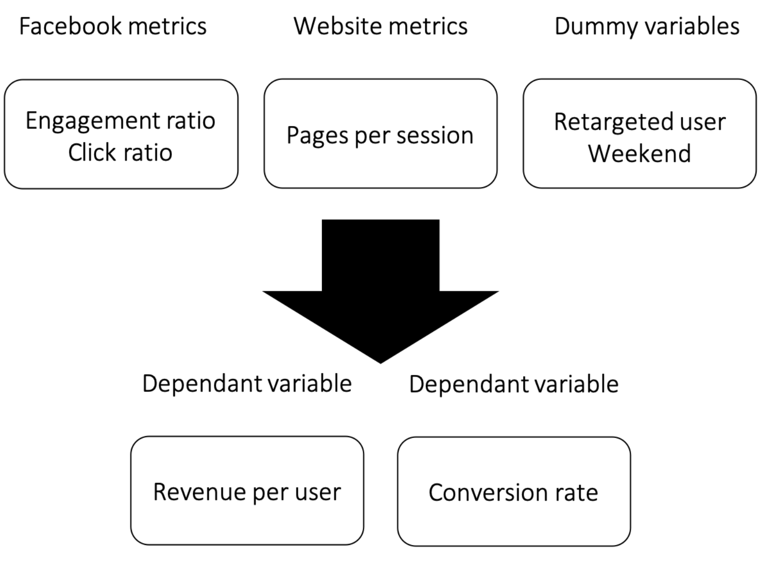
To further examine the relationships between the variables, four different regression analyses are needed. In a nutshell the regression analysis aims to model the variance in dependent variable with the variances of independent variables. Basically, trying to determine how the independent variables affect the dependent variable. These four analyses will be different in terms of the independent variable used, as well as the user groups studied. The groups were coded with two dummy variables, Retargeting and Returning, making the fresh audience control group in terms of the effect of previous brand exposure. The additional dummy variable weekend is added to study possible seasonality of user behavior as it can assumed that people would have more time for online shopping during the weekends. So even if this ends up not being the case, it is important to take into account to guarantee the quality of the findings from the regression analyses. Also, there are two different dependent variables, revenue per user and conversion rate, to further study how different variables are related and explain user behavior.

4.8. Fresh Audience and Retargeted Audience – Regression Models 1 and 2

Figure 19

Illustration of the Design of Regression Models 1 and 2

Fresh Audience and Retargeted Audience



For the fresh and retargeted audiences the effect of Facebook metrics have to be analyzed, so the returning audience group will be excluded from the regression analyses 1 and 2. So the regression analyses are designed as the figure 19 above illustrates to analyze and model the effects independent variables from both Facebook and website analytics have on average revenue per user and average conversion rate.

Figure 20

Correlations Table for Variables

Fresh Audience and Retargeted Audience

		Revenue/users	Pages per session average	Conversion rate	Clicks/impressions	Engagement/impressions
Revenue/users	Pearson Correlation	1	.096	.960**	.190*	-.026
	Sig. (2-tailed)		.291	.000	.034	.771
	N	124	124	124	124	124
Pages per session average	Pearson Correlation	.096	1	.082	-.363**	.139
	Sig. (2-tailed)	.291		.366	.000	.123
	N	124	124	124	124	124
Conversion rate	Pearson Correlation	.960**	.082	1	.231**	.005
	Sig. (2-tailed)	.000	.366		.010	.955
	N	124	124	124	124	124
Clicks/impressions	Pearson Correlation	.190*	-.363**	.231**	1	-.115
	Sig. (2-tailed)	.034	.000	.010		.205
	N	124	124	124	124	124
Engagement/impressions	Pearson Correlation	-.026	.139	.005	-.115	1
	Sig. (2-tailed)	.771	.123	.955	.205	
	N	124	124	124	124	124

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

The figure 20 illustrates the independent correlations between the variables taking the Fresh Audience and Retargeted Audience into account. At the first glance it looks like the Facebook metrics (engagement rate and click rate) have no significant correlation or even negative correlation to website behavior metrics (revenue per user and conversion rate). This might be caused by the rather large reach of the Facebook advertising, especially when targeting Fresh Audience, and relatively small engagement and click rates these campaigns achieved on average. Additionally, revenue per user and conversion rate have significant positive correlations as can be expected. These variables will be targeted with regression models independently to make sure regression analysis is as reliable and useful as possible.

Figure 21

Regression Model 1 for Revenue per User

Fresh Audience and Retargeted Audience

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.368[a]	.135	.098	1.238735410012195	1.818

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	28.288	5	5.658	3.687	.004[b]
Residual	181.067	118	1.534		
Total	209.355	123			

Dependent Variable: revenue per user
Predictors: (Constant), Weekend, Retargeted, Pages per session average, clicks/impressions, engagement/impressions

Coefficients

	Unstandardized	Coefficients	Standardized Coefficients			Collinearity	Statistics
	B	Std. Error	Beta	t	Sig.	tolerance	VIF
(Constant)	-.719	.757		-.950	.344		
Retargeted	1.441	.480	.554	3.003	.003	.215	4.649
Weekend	.082	.249	.031	.330	.742	.817	1.225
Engagement/impressions	-3.083	18.282	-.015	-.169	.866	.912	1.097
Clicks/impressions	-72.224	61.322	-.222	-1.178	.241	.207	4.832
Pages per session average	.371	.160	.220	2.315	.022	.811	1.233

The figure 21 illustrating the regression model 1 on revenue per user for the fresh audience and retargeted audience. As can be seen from the rather low adjusted R square value, 0.098 these independent variables are not that good at explaining the variance in revenue per user. However, as the Sig value on ANOVA table is 0.004 which is well beyond the 0.05 threshold for significance, this model is still statistically significant, just not that good.

From the standardized coefficients beta values, it can be seen that both Facebook-metrics, Clicks/impressions and engagement/impressions actually have negative effect on the revenue per user meaning that the Facebook advertisement measurements are not effective at forecasting revenue. This supports rejection of Hypothesis 4. However, the previous engagement with the brand, in this case being targeted with the retargeting advertisements seems to have positive, significant effect (Beta = 0.554) on revenue per user. This finding provides further evidence supporting Hypothesis 2.

Similarly, pages per session average has beta value of 0.220, meaning it also has positive effect on revenue per user. This supports Hypothesis 3.

However, it is worth noting again that as a whole this model only explains 9.8% of the variance in revenue per user making the whole model rather insignificant.

Figure 22

Regression model 2 For Conversion Rate

Fresh Audience and Retargeted Audience

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.389[a]	.151	.115	.007733962889944	1.698

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	.001	5	.000	4.197	.002[b]
Residual	.007	118	.000		
Total	.008	123			

Dependent Variable: conversion rate
Predictors: (Constant), Weekend, retargeted, Pages per session average, clicks/impressions, engagement/impressions

Coefficients

	Unstandardized	Coefficients	Standardized Coefficients			Collinearity	Statistics
	B	Std. Error	Beta	t	Sig.	tolerance	VIF
(Constant)	-.005	.005		-1.148	.253		
Retargeted	.009	.003	.553	3.026	.003	.215	4.649
Weekend	.001	.002	.064	.684	.495	.817	1.225
Engagement/impressions	.017	.114	.013	.152	.880	.912	1.097
Clicks/impressions	-.381	.383	-.186	-.996	.321	.207	4.832
Pages per session average	.002	.001	.209	2.224	.028	.811	1.233

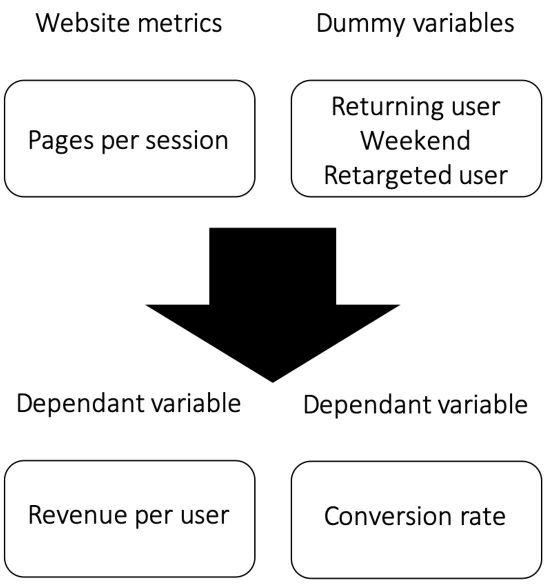
The figure 22 illustrates the regression analysis 2, which models the effects on conversion rate for the fresh audience and retargeted audience. The adjusted R square of the model is 0.115 making it rather weak model. However, as the ANOVA table shows, the model has Sig value of 0.002 making it statistically significant.
From the coefficients table it can be seen that the previous brand exposure i.e. retargeted variable is the most notable predictor of conversion rate (Beta = 0.553) further supporting Hypothesis 2.
In addition to brand engagement, pages per session average has also significant positive effect (Beta = 0.209) on conversion rate among these two audience groups. This finding supports Hypothesis 3.
As the role of Facebook engagement rate (likes and comments) has no significant effect on conversion rate (Beta = 0.013), there is strong evidence in favor of rejecting Hypothesis 4.

4.9. All Audience Groups – Regression Models 3 and 4

Figure 23

Illustration of the Design of Regression Models 3 and 4

Fresh Audience, Retargeted Audience and Returning Audience



When it comes to analyzing all of the groups, figure 23 above illustrates how the regression analyzes 3 and 4 are designed. As described above, independent and dummy variables are used for the regression analysis to analyze and model the effect they have on the average revenue per user and average conversion rate. As these models take only into account the website behavior metrics, all three audience groups are included into analyses.

Figure 24

Correlations Table for Variables

Fresh Audience, Retargeted Audience, Returning Audience

		Pages per session average	Revenue/users	Conversion rate
Pages per session average	Pearson Correlation	1	-.038	.339**
	Sig. (2-tailed)		.607	.000
	N	186	186	186
Revenue/users	Pearson Correlation	-.038	1	.818**
	Sig. (2-tailed)	.607		.000
	N	186	186	186
Conversion rate	Pearson Correlation	.339**	.818**	1
	Sig. (2-tailed)	.000	.000	
	N	186	186	186

** Correlation is significant at the 0.01 level (2-tailed).

The figure 24 above illustrates the correlations in website behavior metrics for all the audience groups. Naturally taking the Returning audience also into account significantly influences these metrics. Based on these correlations, there seems to be interesting and significant (0.339 at 99% confidence rate) positive correlation between pages per session average and conversion rate. Naturally the conversion rate has significant and strong positive impact on the revenue (0.818 at 99% confidence) and that is why there will be separate regression models targeting these variables one at the time to avoid them influencing the reliability of the regression models.

Figure 25

Regression Model 3 for Revenue per Customer

Fresh Audience, Retargeted Audience and Returning Audience

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.772[a]	.597	.588	1.073935814822490	1.666

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	308.697	4	77.174	66.914	.000[b]
Residual	208.754	181	1.153		
Total	517.452	185			

Dependent Variable: revenue/users

Predictors: (Constant), Weekend, returning, retargeting, Pages per session average

Coefficients

	Unstandardized Coefficients		Standardized Coefficients			Collinearity	Statistics
	B	Std. Error	Beta	t	Sig.	tolerance	VIF
(Constant)	-.630	.277		-2.278	.024		
Weekend	-.054	.177	-.015	-.308	.758	1.000	1.000
pages per session	.232	.069	.165	3.355	.001	.916	1.091
Retargeting	.860	.197	.243	4.366	.000	.719	1.391
Returning	3.152	.201	.891	15.681	.000	.690	1.448

Figure 25 illustrates the results of the regression analysis 3 which models changes in revenue per user among all groups. As can be seen from the figure 25, the model explains 58.8% of the changes in variance (adjusted R square = 0.588) of dependent variable, revenue per user. Additionally, the ANOVA table shows that the regression model is significant (Sig. value = 0.000 < 0.05).
From the Coefficients table it can be seen that pages per session, retargeting and returning are significant variables for the model (Sig. values 0.001, 0.000 and 0.000 respectively, all below 0.05), while weekend is not significant with Sig value of 0.758 (above 0.05). form the Standardized coefficient Beta values it can be seen that returning (Beta = 0.891) has the most significant, positive effect on the variance in dependent variable (B = 3.152), revenue per user. So, the previous engagement with the brand is a strong indicator that the customer is likely to spend more money on the webstore, especially if the customer is returning to the site on their own. Additionally, retargeted has similarly significant (Beta = 0.243) positive effect on revenue further confirming that the effect of previous engagement to the spending behavior. These findings provide strong support for Hypothesis 2.
Additionally, pages per session has Beta value of 0.165 meaning that there is moderate but positive correlation between the number of pages viewed on the website and the revenue per user. This finding supports Hypothesis 3.

Figure 26

Regression Model 4 for Conversion Rate

Fresh Audience, Retargeted Audience and Returning Audience

R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
.747[a]	.557	.548	.006895358864046	1.604

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	.011	4	.003	56.969	.000[b]
Residual	.009	181	.000		
Total	.019	185			

Dependent Variable: conversion rate

Predictors: (Constant), Weekend, returning, retargeting, Pages per session average

Coefficients

	Unstandardized Coefficients		Standardized Coefficients			Collinearity	Statistics
	B	Std. Error	Beta	t	Sig.	tolerance	VIF
(Constant)	-.014	.002		-7.931	.000		
Weekend	-.001	.001	-.062	-1.256	.211	1.000	1.000
Pages per session average	.005	.000	.530	10.256	.000	.916	1.091
Retargeting	.008	.001	.356	6.097	.000	.719	1.391
Returning	.017	.001	.794	13.342	.000	.690	1.448

The figure 26 above illustrates the regression model 4 which models the effect on conversion rate among all the audience groups. From the adjusted R square value of 0.548 we can see that the model is good at explaining the changes in conversion rate as it explains over half of the changes in variance. Also, the ANOVA show that the model is significant with Sig. = 0.000 which is well below 0.05 threshold.

From the coefficients table it can be seen that all independent variables, but weekend are statistically significant with Sig values well below 0.05 while weekend has Sig value of 0.211.

The standardized coefficients beta table tells that being returning customer has the highest impact on conversion rate (Beta = 0.794) and also being retargeted user has smaller but positive impact (Beta = 0.356). Again, these finding further support Hypothesis 2.

Pages per session average has beta value of 0.530 making it rather significant predictor of conversion rate. This means that the more pages users go through, the more likely they are to purchase. This supports Hypothesis 3.

4.10. Summary of the Findings

To sum up the findings, there are statistically significant differences in the customer behavior between these groups. From all the regression analyzes it can be concluded that the previous engagement with the brand is the strongest indicator of higher revenue per customer as well as higher conversion rate. This means that the Hypothesis 2 (H2: The deeper the engagement with the brand, the more valuable the customers are in terms of the sales revenue.) will be accepted. Additionally, the time spent on exploring the website i.e. average pages per session, has positive impact on both revenue per user and conversion rate. However, the effect on conversion rate is significantly stronger. This is especially evident when analyzing only the fresh audience and retargeted audience. When the returning audience is taken into account, the size of the effect weakens, but still exists. This means that there was partial support for Hypotheses 3 (H3: More time spent on the website engaging with the brand leads to higher conversion rates and revenue.). On the one hand, there is support for it in the audience segments with lower brand engagement as can be seen especially from the regression model 2 where time spent on website had significant correlation with conversion rate. On the other hand, the correlation with time spent on website and conversion rate and revenue per user was rather insignificant in regression models 3 and 4. There seems to be a point in engagement where more time spent on website does not correlate with conversion rate and revenue anymore, but further studies are needed to uncover more reliable findings on that.

It is quite evident from the regression analyses that Facebook metrics, engagement rate and click rate have no effect on the behavior on webstore. However, retargeted advertisements perform significantly better at generating traffic to the website than advertisements targeting fresh audience. In terms of the Facebook post engagement, i.e. likes and comments, there's no statistically significant difference between fresh and retargeted audience. Based on this, there is partial support for Hypothesis 1 (H1: Previous engagement with the brand leads to higher engagement with the Facebook advertisements.). H1 could be divided so that H1.1: Previous engagement with the brand leads to higher likelihood of clicking brand's Facebook advertisement, which would be accepted and H1.2.: Previous engagement with the brand leads to higher on-site engagement with the Facebook advertisements (meaning likes and comments) which would be rejected.

Furthermore, the Facebook post engagement does not affect the website behavior either as was clearly evident in regression models 1 and 2. This means that the Hypothesis 4 (H4: Facebook engagement (likes and comments) have positive effect on webstore revenue and conversion rate) will be rejected. Last but not least, the time of the week, weekend versus weekdays has no effect on customer behavior, so there is no seasonality effect in customer behavior at least on weekly scale. Based on this study it cannot be concluded whether for example seasonal sales or time of the year affect customer behavior, so further studies are required in those topics as well.

5. DISCUSSION

This section will discuss the theoretical implications of the research findings by connecting them to the existing literature. Reasons why the findings line up with the previous research or contradict some of the existing frameworks will be discussed.

The first and most significant finding from the Facebook and website data is the strong correlation between the previous engagement and the revenue per user and conversion rate. There was clear, significant correlation between variables indicating previous brand engagement and conversion rate and revenue per user supporting Hypothesis 2 and leading to its acceptance.

It's clear that both returning audience and retargeted audience have higher spending and conversion rate than the fresh audience which was used as control group in this sense. For the retargeted audience it seems clear that the retargeted, repetitive marketing messages positively affect the purchasing and spending behavior as Dehghani and Tumer (2015) as well as Kumar et al. (2015) have theorized before. So as Hypothesis 2 was based on these studies, the evidence supporting Hypothesis 2 also signify that these studies are still relevant and applicable. It is also worth noting that as retargeting on Facebook falls into the repetitive marketing message exposure, there was no evidence found that repetitiveness of marketing messages would hurt the initial positive brand perception as for example Chatterjee et al. theorized (2003), actually quite the opposite as the both conversion rate and revenue per user improved significantly compared to the fresh audience. So at least based on this study, Facebook advertising significantly differs from the online banner advertising Chatterjee et al studied. Additionally, for example Brettel et al. (2015) highlighted the importance of giving the audience on social media platforms the power to choose to what degree and how they want to engage with the company on the platform. Furthermore, they found that what they called "stream impressions" which translates to for example Facebook advertisements that blend in with other content on the platform have negative effect on purchase intention and sales. In the light of the findings from this study, it is safe to say that Facebook advertising is indeed effective, even if the audience has not made the choice to engage with the company.

In case of returning audience, which has even higher revenue per user numbers, there is no repetitive marketing messages attracting the audience back to the website, but rather they return on their own. So, in this case it is safe to assume that these are the most engaged customers and they indeed are the most valuable customers to the company based on revenue per user and conversion rate. As there was significant support for Hypothesis 2 and it was accepted, strength of brand relationship or engagement and value for company clearly correlate. This supports the theoretical framework presented by Villanueva et al. (2007) who proposed that the customers acquired through advertisements (retargeted audience in this case) have more short-term value for the company (as they click the advertisement and proceed purchasing) while the more deeply engaged audience (i.e. returning audience) have more long-term value (returning to the site on their own and having higher average revenue per customer). Additionally, this lines up with the findings of Campbell and Keller (2003) and Palmatier et al (2006), who highlighted the value of consent and initiative from the audience when interacting with the brand. So as their research found, when customers take the initiative and interact with the brand, they are much more valuable customers to the company. Another thing to note is that it is also likely that the company needs to use less resources for marketing and customer relationship management for these customers making them even more valuable.

The correlation between brand engagement and higher spending behavior and conversion rate lines up well with the previous research and frameworks and acceptance of Hypothesis 2 bring more empirical evidence supporting the relevance and applicability of these previous studies (e.g. Campbell & Keller, 2003 and Kumar et al., 2015) further supporting the need for customer relationship management also in digital channels.

What was more surprising was the clear, positive correlation between time spent on the website and revenue and conversion rates, especially when studying the audience groups targeted with Facebook advertising. It seems like these less engaged audience groups need more information about the brand and the products before purchase. This can be tied into previous studies on the importance of brand engagement in influencing purchase decision (Dehghani & Tumer 2015), Kumar et al. 2015). These studies would clearly support the Hypothesis 3, but from the empirical analysis, it seems that the relationship between strengthening brand relationship by engaging with the company's website and customer's purchase intention and value are not as straightforward as previous research would suggest.

Kumar et al (2015) and Dehghani and Tumer (2015) found that the firm-generated content on social media, which is comparable to the Facebook advertisements, indeed positively affects consumers' brand consideration and purchase intention. Based on the findings of this study, it seems that it is necessary that the fresh and less-engaged audience is offered substantial information about the brand and its products and services on the website to further support and amplify this positive change in brand consideration. It is safe to say that the website content has equally important role with Facebook advertisements in converting Facebook audience into customers. What design element or content in this case particularly drives the fresh and retargeted audience to spend more time and later money on the website is impossible to say based on this study. However, it might be that when audience spends time on the website learning about the brand, it might be, consciously or not, considered as brand engagement and they feel invested in the brand and the company and their purchase intention is driven up because of that.

Also, taking the action to click Facebook advertisements is a way of social media engagement, which, as studied by Campbell and Keller (2003), leads to higher brand loyalty and eventually higher customer lifetime value (Kumar et al., 2015). So, in the light of these studies, just having people clicking the advertisement and going to the website can be considered success as it sows the seeds of abovementioned brand loyalty and higher customer lifetime value.

The fact that the role of pages per session average has on revenue and conversion rate diminishes when the returning audience is taken into account on regression models can be explained by the exceptionally high conversion rate and revenue per user of the returning audience. The main attribute of this audience group is that it is indeed returning to the website, so it can be assumed that they have spent time interacting on website before and have established the brand loyalty as described by Campbell and Keller (2003). It is also likely that they have initially found their way to the website via Facebook advertising (including Facebook and Instagram) as it is by far the dominant source of fresh website traffic (figure 27, 48% of all new users come via Facebook and Instagram advertising) Based on that, it can be assumed that these users are further on in customer journey and thanks to the already established brand engagement and loyalty move more directly to conversion when returning to the website. In a sense they could be done with their brand consideration and thus do not need so much information (i.e. time on website) to come up with purchase decision.

Figure 27

Illustration of Biggest Channels of New users to the Website (Google Website Analytics of Company X)

Source of Traffic	Number of NewUsers	% of All New Users
Google Advertisement	10 022	26 %
Instagram Advertising	7 592	20 %
Facebook Advertising	10 757	28 %
Google Organic Search	4 123	11 %
Other	5 445	14 %
All New Users	37 939	100 %

Furthermore, what Brettel et al. (2015) seems to get right is that exposure to Facebook content of the company, like advertisements creates long term increases in sales. This is likely due to the link between brand engagement and brand loyalty discussed earlier. In this light, it is ever more likely that the returning audience has previous engagement with the brand's social media content and now they are expressing the results of positive impact on sales Brettel et al. (2015) described.
Overall this study presents new insights into the performance of Facebook advertising which is largely applicable to other social media sites as well. Based on the data analysis conducted, it is clear that the social media engagement with the brand in a sense of attempting to maximize the likes and comments on company's content is not crucial for the advertisement performance. It is clear that the likes and comments have no effect on brand consideration, webstore behavior nor purchasing. As rejection of Hypothesis 4 and partial rejection of Hypothesis 1 based on the empirical evidence found in this study prove, engagement with Facebook content in a sense of liking and commenting is not a reliable or relevant measurement of performance. So, in a sense the idea that the social media content needs to be engaging and get as many likes and comments as possible seems outdated or not applicable to this case. Furthermore, even the people in the social media advertising business have started to realize that focusing on engagement and community building actually doesn't suit all companies (Halme, 2018).
Additionally, the behavioral insights into how the previous engagement with the affects the behavior on social media and further on webstore have not been studied to this extent before. Especially the comparison between the retargeted audience and returning audience gave new and novel insights proving that not all previous engagement is the same. This also proves that for example the way Brettel et al. (2015) studied the effect of social media by just looking how the total numbers of for example engagement or impressions affect sales is not relevant way to study effectiveness of social media. This can also be reflected in a way that empirical analysis lead to partial rejection of Hypothesis 1 as described before. Hypothesis was rejected in terms of previous engagement having effect on future liking and commenting of Facebook content, but there was a clear connection supporting relationship between previous engagement and likelihood of future clicking on Facebook content from the brand. So, in addition to not all previous engagement being equal, a key takeaway for researchers and practitioners of Facebook advertising from this study is

that not all Facebook engagement is same either and likes and comments seem to be less relevant than clicks for indicating the performance of advertisements campaign.

There needs to be more emphasis on audience characteristics in order to understand how individual audience members behave. In addition to academics, this is crucial also from the practitioner point of view as Facebook among others allow the individual level personalized targeted advertising messages, so the individual level understanding is needed as well to utilize these tools and understand the results.

6. CONCLUSIONS AND MANAGERIAL IMPLICATIONS

Based on the findings of website data and similar to what previous research has concluded, prior brand engagement is indeed the strongest indicator of brand consideration and purchase intention (Kumar et al., 2015 and Sanne & Wise, 2018). But it is worth noting that among the lower-engagement audience segments, time spent on the website (average pages per session in this case) has a significant, positive effect on especially conversion rate but also on revenue per user.

However, it is important to keep in mind that these lower-engagement customers have clicked themselves through the Facebook advertisement ending up at the company website, so they should have some interest towards the brand and its products so their brand consideration (according to Sanne & Wise, 2018) has already shifted to be more favorable. Further on more time spent on the website increases the positivity towards the brand improving brand consideration and eventually leading to purchase intention like Sanne & Wise (2018) described.

Whether the effect that higher pages per session value can have on the purchase behavior of website users equals with the effect of higher levels of prior brand engagement remains unknown. It might be possible with engaging website design and content to achieve significant increases in purchase behavior especially among the fresh audience and retargeted audience. As mentioned before, the returning audience is likely further on in the customer journey and offers an unfair comparison point with the significantly higher brand engagement and brand consideration or even brand loyalty.

What comes to the customer engagement theory as a whole? Despite all fuss around empowering and amplifying customers actions and voices, it seems that, at least in social media setting, customer engagement is way less interactive and dialogue-like than many practitioners and academics believe. At least in the case of company X, customers seem to be more passive receivers of information rather than actively participating and interacting with the brand by for example linking, commenting and sharing content to spark discussion and voice their opinions. While social media offers a great platform for empowering customers to become voices for brands and micro-scale opinion leaders, it seems that more individual firm-customer relationship and communication is what gets audience engaged with the brand and converting to customers. Providing customers plenty of information about the brand and its products for example with brand-focused advertising and information-rich website evidently leads to more time spent on website and strengthens the firm-customer relationship even leading to purchases. After the initial interest and information-gathering, as previous research has shown, continuous communication for example in the form of retargeted advertisements improves the conversion rate and revenue per user on the webstore significantly comparing to the new audience. In this sense this case study suggests that in order to create valuable customer engagement, firms should focus on one-on-one communication with the potential and existing customers and personalize the communication goals and messages based on receivers status on customer journey instead of trying to push the collectivity of brand engagement or pushing the customers to become the brand ambassadors and influencers for the brand.

When thinking about the actionable managerial implications, there are two main points; retargeting and time spent on the website. Even though the people retargeted with Facebook advertising don't quite match the returning audience in terms of the conversion rate or revenue per user, they are still much more valuable customers than completely fresh audience. Even though the case company is still up and coming and mainly using advertising as a way of building brand image, it seems clear that retargeting is already viable tactic to reach the audience that is interested in the brand put needs a little push to convert into customers. In the business point of view retargeting is also very lucrative as it is cheaper to reach this smaller, more revenue generating audience with Facebook advertising.

Additionally, when thinking about the customer journey, it seems natural that the first touchpoint with the brand establishes the connection with the brand and improves brand consideration and then the second, retargeted touchpoint focuses on creating the conversion thanks to the improved brand consideration and established relationship with the brand. Very much in line with what for example Sanne & Wise (2018) described in their study.

What comes to the time spent on website, it seems like the less engaged audience group is the more time they spend on the website, i.e. go through more pages per session. In addition to that, the more pages they go through the more likely the session leads to conversion. So, it seems that the website design and content have crucial roles in converting the low-engagement audience groups. In practice for example making the website very easy to navigate and promoting the different contents, like other similar products, on the website might increase the pages per session and likely the conversion rates as well. In other words, the website content and design should be considered as a continuation from the Facebook advertisements and encourage users to explore as much of the site as possible. This is most likely a very good way to improve the performance of retargeted audience compared to the returning audience which otherwise has superior conversion rates and revenue per user numbers.

All in all, building this sort of continuous interaction with the customers, even with Facebook advertisements and website content, along the customer journey supports the improved brand consideration and loyalty by strengthening the customer-firm relationship and leads to higher customer lifetime value.

7. LIMITATIONS OF RESEARCH

Maybe the biggest challenge for this study was posed by the difficulty to connect data from different sources. Data from Facebook was formatted on advertisement campaign basis and the data from website analytics was mainly ratios and averages for different audience groups. Because of that, tracking individual users from Facebook to the website was impossible. Because of that, the audience had to be analyzed based on their previous engagement to the brand instead of other metrics. Most of the flaws or inaccuracies in the study are rooted in this problem, so in essence more co-operative analytical platforms would be needed to more accurately analyze the behavior of customers on individual level.

Having access to tracking individual users' behavior from Facebook to the webstore would have allowed to more detailed analysis on for example optimal landing pages and optimal time spent on website instead of settling into using averages instead. Unfortunately, both Facebook and Google keep the information on individual-level customer behavior to themselves. This is most likely due to the business reasons, as especially Facebook sells advertising service that is heavily based on company's analysis on customer behavior so showing the open data to others would compromise their business. As people's reactions to Facebook advertisements is really hard to study in controlled environment, the research in this are needs to settle for inaccuracies at least for now.

In addition to that, there were two main shortcomings on the Facebook side of things that should be further studied in the future; the effect of the content of advertisements and the effect of different types of previous engagement. There is prior research on how advertisement content affects audience behavior (e.g. Kantola, 2014) and there is research on how for example social media engagement affects purchase behavior (e.g. Dehghani & Tumer, 2015) but there is no comprehensive study on how these attributes are interconnected and affect the purchase behavior. As obtaining high quality data to do the comprehensive research is more than challenging, the lack of studies is understandable but a significant blind spot in academic understanding of online advertising purchase behavior.

For future research, it is highly recommended to use a case companies that have taken the best possible advantage on Facebook's tracking pixel on their webstore as it makes it possible to better track the customer behavior from Facebook to webstore and more comprehensively evaluate the performance of advertisement campaigns. Additionally, recording the creative side of the advertisements studied, i.e. the visuals and texts, would make it possible to analyze more of the relevant variables and their effect to the advertisement performance all the way to the purchase behavior of target audience. Furthermore, if possible, the target groups of different advertisement campaigns should be as little overlapping as possible, in order to be able to evaluate how target audience demographics might affect advertisement campaign performance.

Last, the time period used for data collection could have been longer in order to better explore for example seasonality effects as well as to have overall more reliable findings. The reasoning behind shorter data collection period was the recent advertisement algorithm change on Facebook that basically made all the previous results incomparable to the results achieved after the change. So even though longer-term studies on social media advertising are needed, they are also rather difficult to achieve as companies like Facebook who are running the advertising platforms constantly change their rules and logics making it practically impossible to perform such studies.

All in all, in order to be able to truly study and understand the variables and conditions affecting performance of Facebook advertising and customer behavior, future research should be conducted in closer co-operation with case companies. This way the researchers would have ability to compose the target groups and have more comprehensive control over the advertising as it is made to produce reliable and rich data that can be analyzed in greater detail. This would make it possible to gain truly uniquely comprehensive understanding on both social media advertising with all of its sides as well as on customer behavior on digital platforms and webstore environment.

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